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Tracking of Maximum Power Point for PV Solar System Based on Adaptive Quantum Neural Controller

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Abstract: The control of maximum power point tracking (MPPT) occupies the top importance in the optimization of photovoltaic systems (PVSs). Due to output power fluctuations in the variance of temperature and irradiance and real variation of climatic conditions, solar panels must mostly have nonlinear behavior. Consequently, an efficient control technique is vital to achieve maximum power from solar panels during various environmental conditions. In this work, a quantum neural network is adopted to lead the system toward working at the maximum power operating point. Experimental findings show that the proposed technique is efficient and offers a very fast approach in extracting maximum power point compared to the recent related works. The proposed MPPT results imply that it has outstanding dynamic response even in quick changes of temperature and irradiation, and it has very fast tracking time i.e. 37 ms. It is also more accurate than all the related works and the efficiency of tracking the maximum power point is 99%. Hence it is expected to be a promising and superior approach in maximum power point tracking.

Keywords: Solar PV control system, Maximum power point tracking, Adaptive quantum network, Neural controller.

1. Introduction

Solar energy is the most common renewable source for electrical and heat energies. Photovoltaic (PV) cells are extensively used to convert solar energy into electricity. This important sustainable energy source is progressively worldwide used due to its environmental compatibility and its wide abundance [1]. The generated power in case of using photovoltaic solar system is usually lower than that generated by other typical power sources.

The development of PV panels has played an essential role in decreasing the typical power sources and hence in reducing the usage of fossil fuels. Recently, the modern technologies of PV panels have been working toward developing efficient MPPT approaches.

Nowadays, the development of renewable energy production has been becoming the most demanding goal to reduce fuel emissions and to meet clean climate targets. In addition, it is characterized by being inexpensive and very easy to be installed compared to other typical energy sources. These reasons have motivated the researchers to improve the technologies of renewable energy production including solar energy. The efficiency of PVS depends on the climatic factors and the operating point load [2].

Performance enhancement of PV panels requires efficient techniques for MPPT, and this is essential to convey maximum power generated by PV from the source to the load. It could be implemented by managing the converter's duty cycle with different climatic conditions.

The optimization of the energy system is very important to accomplish the maximum power from the PV system for various environmental conditions [3]. Solar power is seriously affected by climatic conditions such as ambient temperature and the intensity of radiation. The changes in these climatic conditions are surely the main reason of shifting the maximum power point in solar panels.

In the literature, several works consider MPPT. Complex approaches for MPPT are proposed and called direct methods. These methods include, perturb and observe (P&O) approach which is proposed by [4-5], and the incremental conductance (IC) approach which is proposed by [6]. The hill-climbing method, which is widely used, is proposed by [7]. In spite of being easy to be implemented, the direct methods have the problem of oscillation around the MPP in addition to their weak ability to track MPP environmental changes.

The fuzzy logic control (FLC) methods have been proposed by many researchers [8-9] and their results demonstrate better performance compared to traditional technologies of P&O and IC. This approach is limited due to its imprecise operating of the position of the PV generator in the operation for MPP. More disadvantages in using the FLC arise from its complexity and high cost of implementation. Moreover, artificial neural networks (ANN) methods have many characteristics such as fast monitoring, offline learning, and stable running. Due to the preceding ANN benefits, many ANN-based approaches have been proposed lately for MPPT with superior results [10, 11].

Another approach called particle swarm optimization (PSO) is extensively used in proposing developed techniques of MPPT. The PSO approaches are stimulated and inspired by group behavior of some types of birds and collective fishes [12-14]. In the PSO technique, the optimal weights could be found by using the swarm intelligence properties. At the beginning of this approach, a matrix is supposed as the initial particle values in the PSO, and then these values are modeled with the vectors of position and velocity in the search space to be then computed as the particle's cost value.

The sliding mode control (SMC) method is very convenient in designing efficient control systems. This method is characterized by being nonlinear, simple, robust, and good dynamic behavior [15, 16]. The SMC method is widely used in many other control fields such as inverter control systems [17], motor control [18, 19], and robotics [20]. These are used to remedy the problems of unknown outer and inner disturbance and probable parametric variations. The SMC is developed by Utkin based on non-linear control theory [21], and it is extensively used with variable structure systems.

Formulation of the conventional particle swarm optimization was used by [22] to decrease tracking time and to lessen the power losses and generated output power oscillation during the process of tracking. This could be accomplished by using a special coefficient for time-varying weighting in the conventional particle swarm optimization (PSO). This approach achieved results with high efficiency i.e. 99.98 % compared to the previous works but with high tracking time: 0.273 s.

A new method based on ANN is proposed by [23]. This method consists of two stages, in the first one the PV panel was generated with optimal voltage while the second stage includes a non-linear adaptive back-stepping control. The second stage approach is efficient in following the optimum voltage by using DC/DC boost converter's duty cycle. The results of this method show that it outperforms most of other related methods in terms of rapidity of tracking time, but it still has the disadvantage of low efficiency compared with the other related works.

A new approach based on a technique of cascade control loop is proposed using the PSO and the SMC to mitigate the drawbacks of conventional MPPT methods [24]. In the first loop, the voltage-power curve is swept to extract the optimum global maximum power point (GMPP), followed by generating corresponding optimal voltage to be considered as a reference. In the second loop, the referenced voltage is tracked by the duty cycle of the single-ended primary-inductor converter.

The performance parameters, some method requirements, such as convergence rate, complexity, speed, required sensors, and cost are considered as the main criteria to evaluate the superiority and feasibility of any MPPT method. A set of tracking parameters, such as measurements comparisons, mathematical calculation followed by intelligent prediction, and trial and error operations are extensively used in the classification as presented in [25]. Based on PVs operational conditions, reference signals are generated and the estimated values are considered as PVSs trajectories. In the case of stable environmental conditions, most proposed MPPT techniques are able to get stable and reliable tracking results. But most of them suffer from low accuracy and unstable MMP particularly in changing climate and loading.

In this work, a quantum neural network is used as a controller to track the MMP of the PV solar system. A boost converter circuit is designed and the overall system including the selected panel was simulated using MATLAB/ SIMULINK environment.

This work is exhibited in the following arrangement: Section 2 describes the proposed PV system and cell modeling; section 3 presents the MPP control scheme with adaptive quantum neural network structure. In section 4, the proposed method results are presented and discussed, while section 5 presents our conclusions.

2. Photovoltaic system description and modeling

A solar cell is a P-N junction electronic device that is used to convert the energy of sunlight to electrical energy. The main basic components of the PV system are the solar cells, and each cell can produce 0.5 volts. To produce a high voltage, several cells are combined in series and called a module. A combination of solar modules, which is known as an array is used to generate the needed power and get the required voltage, where these modules are connected in series and parallel.

2.1 Photovoltaic cell model

The construction of the PV array is built using many parallel strings which are designed based on series PV. Each PV panel is built up by using one or more modules. A number of PV cells, connected in series and parallel, are used to construct each PV panel. The connection is made in a way depending on required power and voltage. The equivalent circuit of solar cells can be represented by two resistances and one diode, one resistance is connected in parallel with the diode while the other one is connected with the cell terminal, as shown in Fig. 1.

This model consists of a diode, a current source (I_L), a shunt resistance (R_{sh}), and a series resistance (R). The PV cell current (I) is expressed by the following equation [26]:

$$I = I_L - (I_o + I_{sh}) \quad (1)$$

The value of photon current (I_L) is based on amount of solar radiation by solar cell. Consequently, the photocurrent value is directly proportional to variation in both temperature and solar irradiance and it is expressed by:

$$I_L = (I_{scr} + k_i \Delta T)\frac{G}{G_r} \quad (2)$$

where I_{scr} is rated solar current, k_i is short circuit temperature coefficient, G is solar irradiance in W/m^2 and Gr is nominal irradiance. The values of the above variables depend on the weather

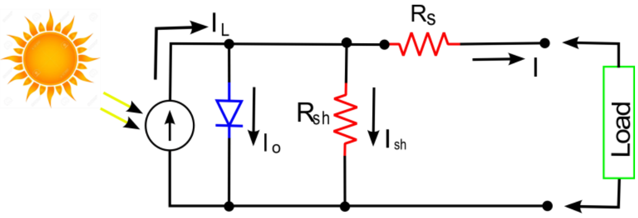

Figure. 1 Equivalent circuit of PV cell

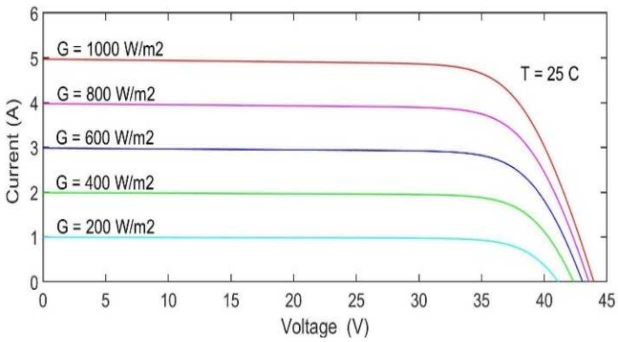

Figure. 2 VI characteristics of PV cell

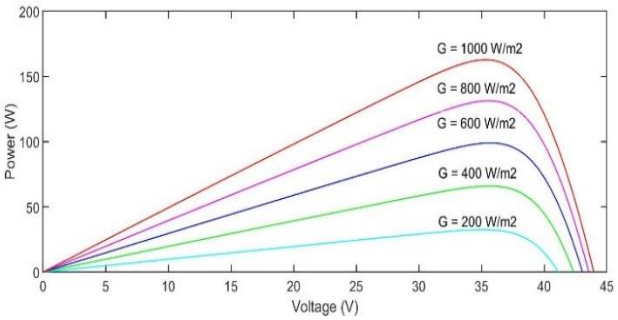

Figure. 3 VP characteristics of PV cell

conditions and the temperature at normal weather conditions is 25° C, and generated power at normal weather is 1000 W/m^2. ΔT is difference of operating temperature and nominal temperature (T–T_{ref}).

2.2 Characteristics of PV cells

To get maximum power and then transfer it from the PV panel to the load, it is essential to know the position of the MPP of operation for certain irradiation and temperature. This point can be obtained from the characteristics of the PV cell. The solar cell has two electrical characteristics. The first one represents the relation between the panel voltage and current as indicated in Figs. 2 and 3 presents the second relationship which states the change of power according to various values of panel voltage.

2.3 Boost converter design

The boost converter is an efficient circuit that can maintain the value of output voltage within the

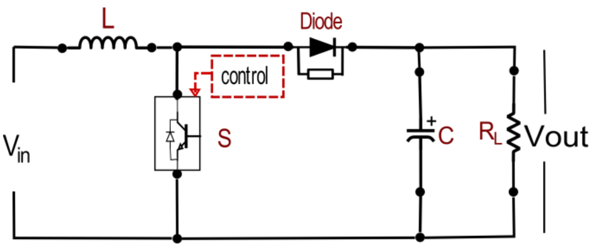

Figure. 4 DC-DC boost converter circuit

desired range. The power delivered to the load can also be under control. The main function of the boost converter, used in the PV system, is to ensure that delivered power to the load is nearly equal to the power generated by the PV panel. Hence, maximum power will be transferred to the load. The components of the boost converter circuit are clearly illustrated in Fig. 4.

The design procedure of the boost converter can be summarized as follows:

1. The input resistance (R_{in}) is chosen in appropriate value that the system operates at MPP. The values of panel current (I_{mp}), and voltage (V_{mp}) at this point will be obtained from the panel specifications. So, the input resistance will be:

$$R_{in} = \frac{V_{mp}}{I_{mp}} \tag{3}$$

2. Choosing the load resistance (R_L) to be larger than the resistance at the MPP.
3. Calculating the duty cycle (D) such that the converter operates at the maximum efficiency (i.e., P_{out}=P_{in}) as follows:

$$I_o = \sqrt{\frac{P_{out}}{R_L}} \tag{4}$$

$$D = \frac{I_o - I_{in}}{I_{in}} \tag{5}$$

4. Selecting the operating frequency of the converter (f_s) and hence:

$$T_s = \frac{1}{f_s} \tag{6}$$

5. Calculating the load current ripple (Δi_L), such that the inductor current equals the load current.

$$\Delta I_L = I_o I_r \tag{7}$$

where I_r is the percentage of current ripple.

6. Choosing the output voltage ripple value as:

$$V_o(ripple) = \frac{\Delta V_o}{V_o} \tag{8}$$

7. The inductance value can be calculated as:

$$L = \frac{V_{in} D T_s}{2\Delta i_L} \tag{9}$$

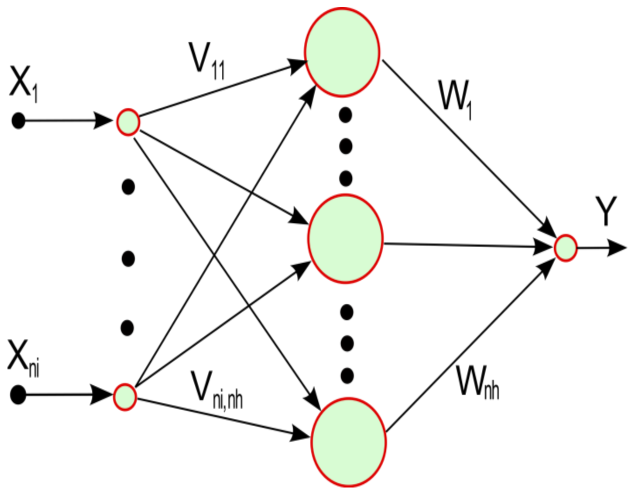

Figure. 5 Quantum neural network structure

8. The minimum capacitance value can be calculated as follows:

$$\frac{\Delta V_o}{V_o} = \frac{D T_s}{RC} \tag{10}$$

So:

$$C = \frac{D T_s}{R(\frac{\Delta V_o}{V_o})} \tag{11}$$

3. MPPT control scheme

The scheme to keep tracking of the MPP is to make the operating point of the converter at the summit of the cure of panel power voltage. This is achieved by controlling the switch of the converter by varying the generated pulses duty cycle according to a certain condition.

3.1 Quantum neural network (QNN) structure and adaptation

The quantum neural network is a feed-forward network that can emulate the behavior of the fuzzy logic structure. The hidden layer of this network has neurons with graded squash function which represents the crisp weighted data coming from the input layer to assimilate the fuzzy memberships as multi-levels of certainty. Fig. 5 shows the structure of the quantum neural network of three layers.

The network consists of three layers. The first layer receives the input vectors (x_i), where i stands for the index of the input vector (x). Every neuron in the hidden layer receives a weighted sum of the input vector and can be evaluated as:

$$ha_j = \sum_i X_i V_{i,j} \tag{12}$$

where haj is the input to the hidden neuron j.

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The output of every hidden layer neuron is passed to a graded compound function which consists of the summation of a number of shifted sigmoid functions. The shift of each sigmoid function specifies the jump to the next level of the quantum-based function. The following function represents the output of hidden neurons:

$$hb_j = \frac{1}{ns} \sum_r f_h(ha_j - \gamma_j^r) \tag{13}$$

where
hb_j= output of hidden neuron j
ns = no. of quantum levels
f_h = squash function of hidden neurons
γ = quantum level shifts
r = index of quantum level shifts

The weights matrix V represents the weights between the input layer and hidden layer, while the matrix W refers to the weights between the hidden layer and output layer, where

$$V_{ni,nh} \in R^{ni\times nh} \tag{14}$$

$$W_{nh} \in R^{nh} \tag{15}$$

where:
ni = input vector size
nh = no. of hidden layer neurons

The jump positions matrix for the quantum hidden units can be represented as

$$\gamma_{nh,ns} \in R^{nh\times ns} \tag{16}$$

The neural network output depends on finding the output node of the output layer by evaluating the result of squash function which receives its input from the hidden layer multiplied by the weights between hidden layer and output layer. To do so, the following equation reveals that.

$$Y = \sum_j hb_j W_j \tag{17}$$

3.2 Quantum neural network scheme for MPPT

The idea behind making the apex of the P-V characteristics curve of the solar cell to represent the P-V system operating is to ensure transferring the maximum power to the load and maintaining the load voltage approximately constant. To accomplish this, a control paradigm is needed. There are many approaches used in this field of application. One of these approaches is the artificial intelligence technique. Neural networks are used widely in many applications and can be used efficiently in solar systems. The quantum neural network (QNN) is related to the group of neural networks and combines between the benefits of learning ability and the reasoning of fuzzy logic.

To make the QNN work as a controller and keep the system operating at the desired point which is the maximum power point, a training process has to be first done. The QNNs contains three layers, namely: input, hidden and output layers. In the input layer, a vector of one variable or more has been received, while the output layer gives the output variable which is the desired output. The training data consists of two vectors: the input vector represents the change of irradiation and the ambient temperature of the panel, while the second vector is the voltage at the point when power is maximum. Fig. 6 shows the QNN structure used in MPPT.

After training, the quantum neural network is ready to be involved in controlling the dc-dc converter such that the system tracks the maximum power operating point for various values of irradiation, temperature, and output power. Fig. 7 illustrates the components of the solar system with the proposed neural network.

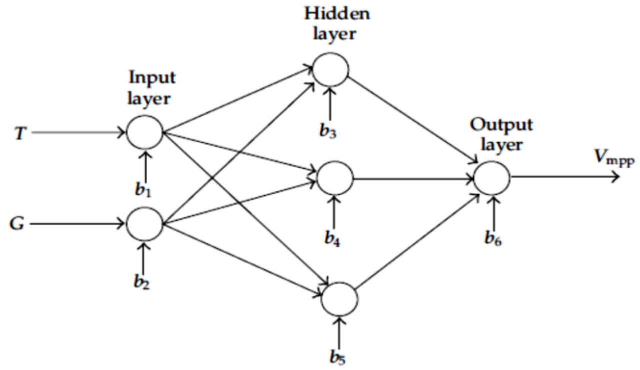

Figure. 6 QNN structure

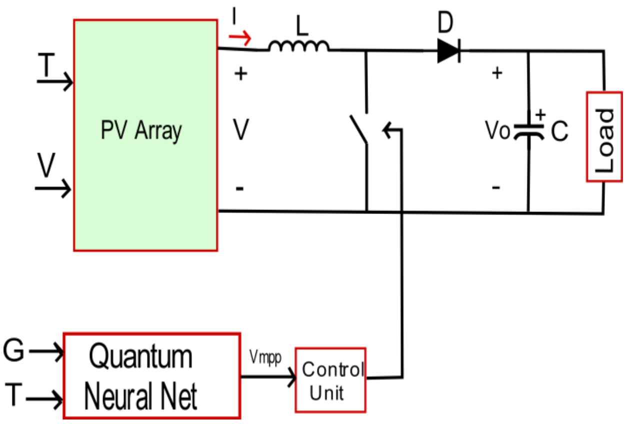

Figure. 7 Block diagram of the controlled solar system under consideration

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4. Results and discussions

In this work, a quantum neural network was designed and implemented to control the MPP and keep tracking this point to ensure transferring the maximum power to the load. For the network training, a collection of data points was extracted by simulating the PV system using MATLAB/Simulink. A range of values for irradiance and temperature of the panel were considered as input to the system while the voltage at maximum power point was the output.

The PV system is composed of a PV Panel, DC-DC boost converter, and load. The PV panel consisted of a single string with two modules per string and Table 1 shows its specifications. Fig. 8 exhibits the curves of the Duty cycle, Load current, Load power, Load voltage, PV Power, and PV voltage for the case of irradiance = 1000 W/m^2, Temperature = 25 ^{0}C, and resistance = 20 ohm. The PV Power curve shows a fluctuation in the transient response and rapidly vanished to reach a steady-state with a settling time equal to 0.1539 seconds and the power reaches a point very close to the maximum power point which is 162.6 W and hence the efficiency becomes 99.8 %.

The DC-DC boost converter components are C1= 100 µf, C2= 470 µf, L= 2 mH, and the switching frequency is 20 kHz. Table 2 explains the parameters of the diode and switch used in the converter circuit.

To examine the reliability of the suggested control technique, various values of panel irradiance, the ambient temperature, and load resistance were used.

Table 3 shows the patterns used to test the PV system.

Table 1. PV panel specifications.

Pmax(W)	Voc(V)	Vmpp(V)	Isc(A)	Impp(A)
162.8	43.92	35.32	5.03	4.61

Table 2. Boost converter diode and switch parameters

Diode parameters		Switch parameters	
Resistance R_{on}	1e-3 ohm	FET resistance R_{on}	1e-3 ohm
Forward voltage V_f	0.8 volt	Internal diode resistance Rd	1e-3 ohm
Snubber resistance Rs	500 ohm	Internal diode forward voltage	0 volt
Snubber capacitance Cs	250e-9 F		

Table 3. Patterns used in testing the PV panel

Pattern No.	G (W/m^2)	T (^{o}C)	R (Ω)
1	1000	25	20
2	1000	25	40
3	1000	40	20
4	1000	40	40
5	600	25	20
6	600	25	40
7	600	40	20
8	600	40	40

Fig. 9 and Fig. 10 present the graphs of panel voltage and power for irradiance equal to 1000 and 600 W/m^2, respectively, for panel temperature of 25 ^{0}C and 40 ^{0}C, and load resistance of 20 and 40 ohms. The aim of taking different values of irradiance, temperature, and resistance is to determine the influence of changing those parameters on the robustness of the solar system.

Table 4 summarizes the most important results by using different patterns which are mentioned in Table 2 and presents the values of PV system characteristics parameters. It’s clear from the table that changing the load resistance has a limited influence on the overall efficiency for the same values of irradiance and temperature.

It is clear that the controller keeps tracking the MPP rapidly after changing the irradiance and temperature of the panel and the longest settling time needed by the system is 0.073 seconds for the case when irradiance = 600 W/m^2 and temperature = 25 ^{0}C. The minimum settling time is 0.037 seconds for the case when irradiance = 600 W/m^2 and temperature = 25^{0}C. Changing of temperature affects the power delivered to the load for the same irradiance. The efficiency is not affected by changing the value of irradiance.

To evaluate robustness and feasibility of our work, the proposed method is compared with five recent related methods. The criteria used in this comparison are the tracking time and the efficiency. The information presented in Table 5 confirms that the proposed method could achieve competitive efficiency among these related works. In addition, the tracking settling time of the proposed method is clearly faster than those of the other related works especially for those of high efficiency.

Fig. 11 shows the PV plots for both voltage and power against time for long run conditions to test the system response to sudden change of irradiance. It is clear that the controller complies quickly and adapts to the new environmental conditions.

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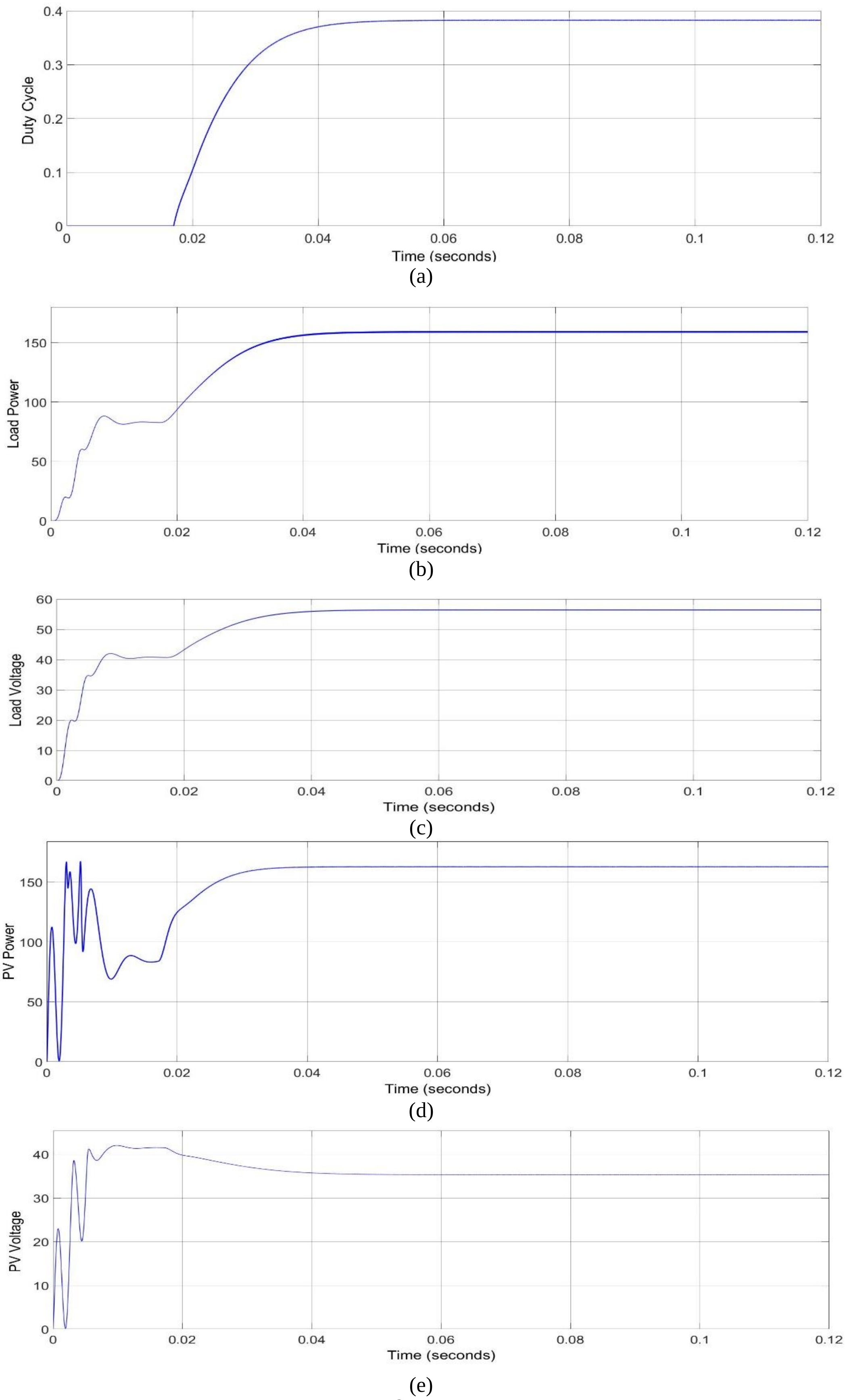

Figure. 8 PV system curves for the case G = 1000 W/m^2, T = 25ºC, R = 20Ω: (a) duty cycle, (b) load power, (c) load voltage, (d) PV power, and (e) PV voltage

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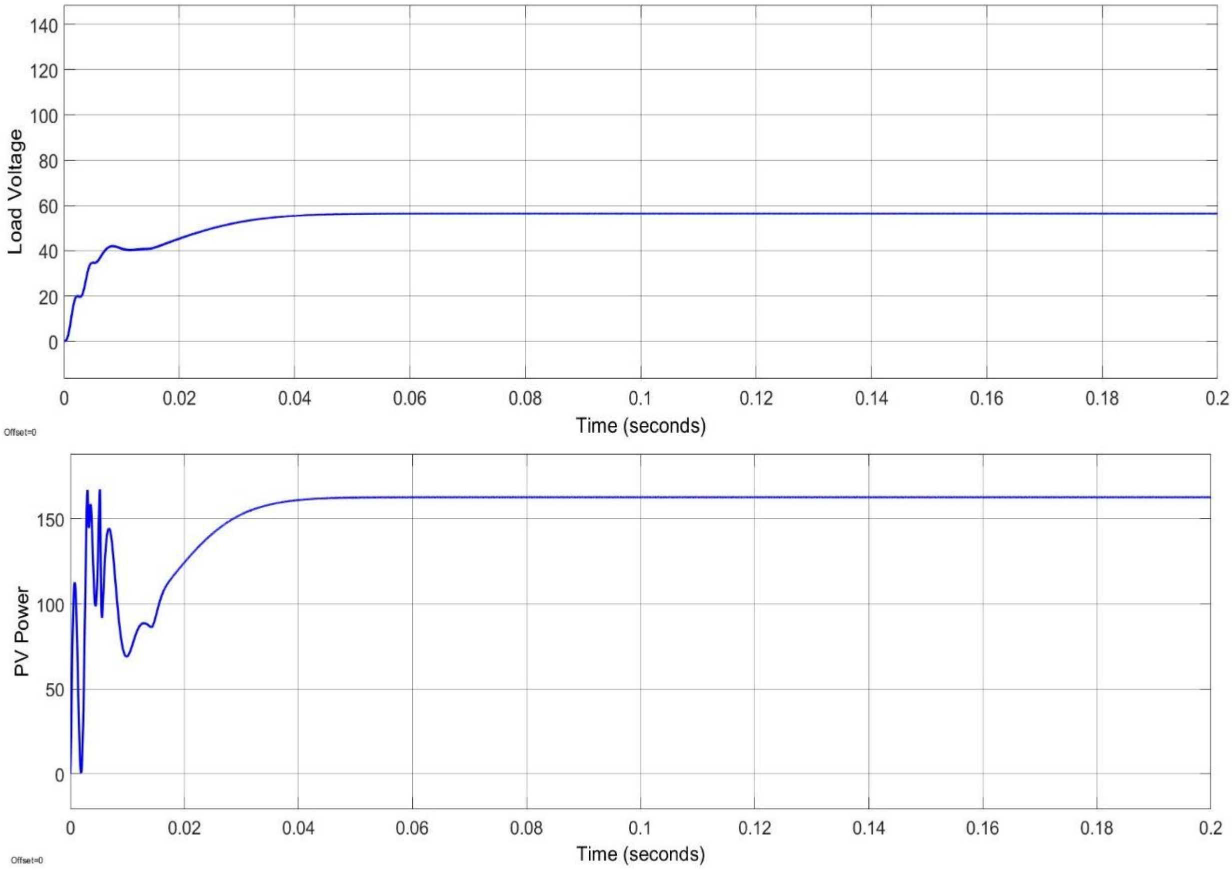
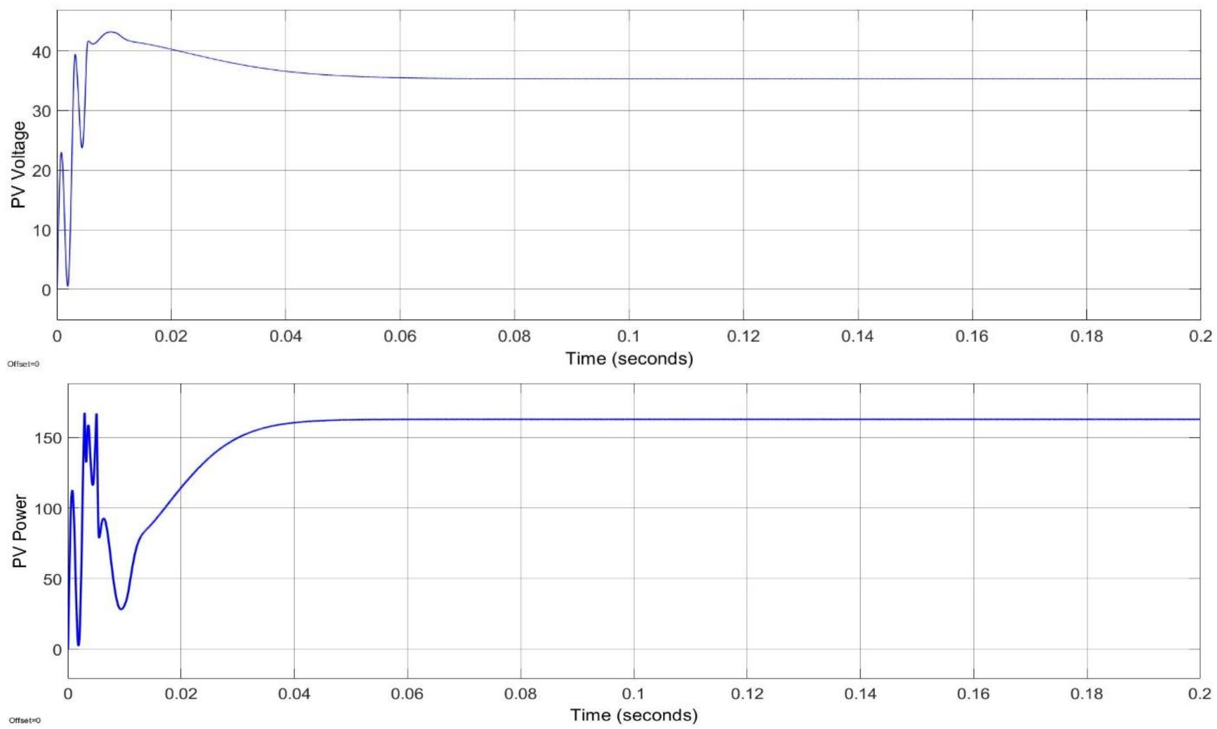

Load Voltage
Time (seconds)
Offset=0
PV Power
Time (seconds)
Offset=0

(a)


PV Voltage
Time (seconds)
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PV Power
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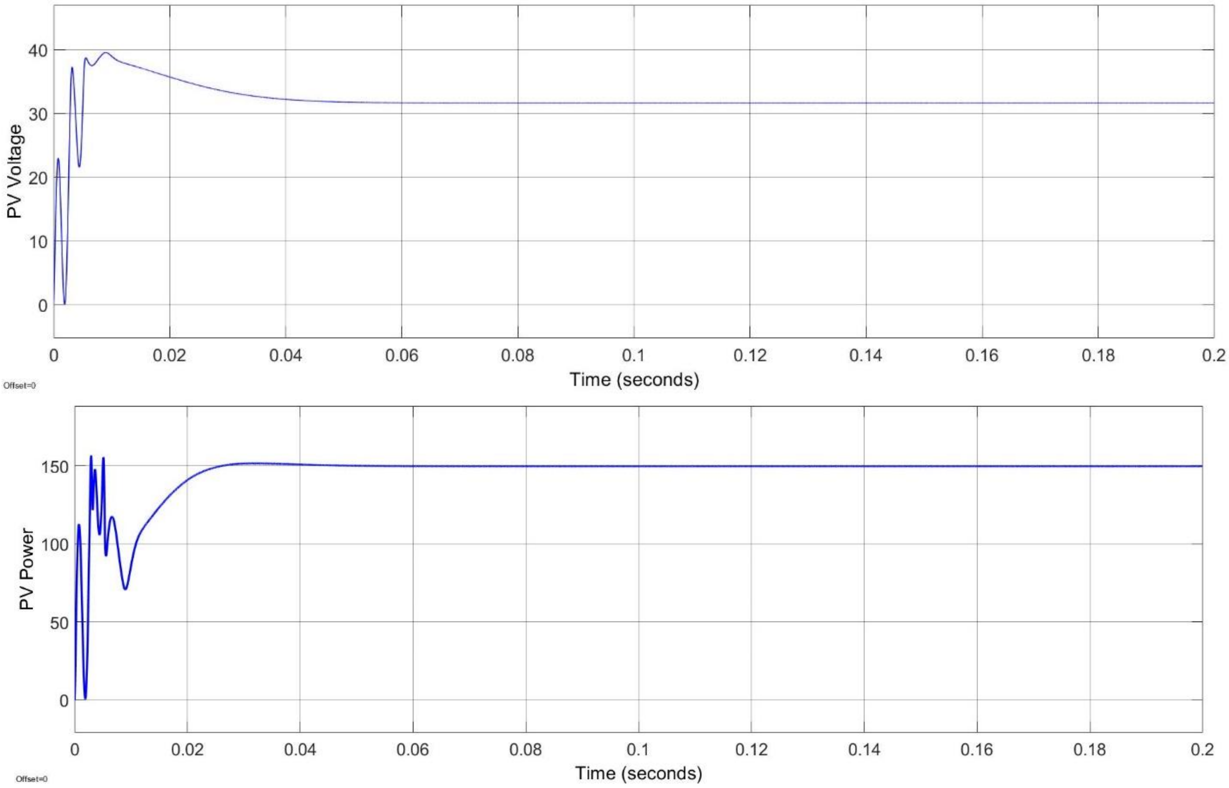
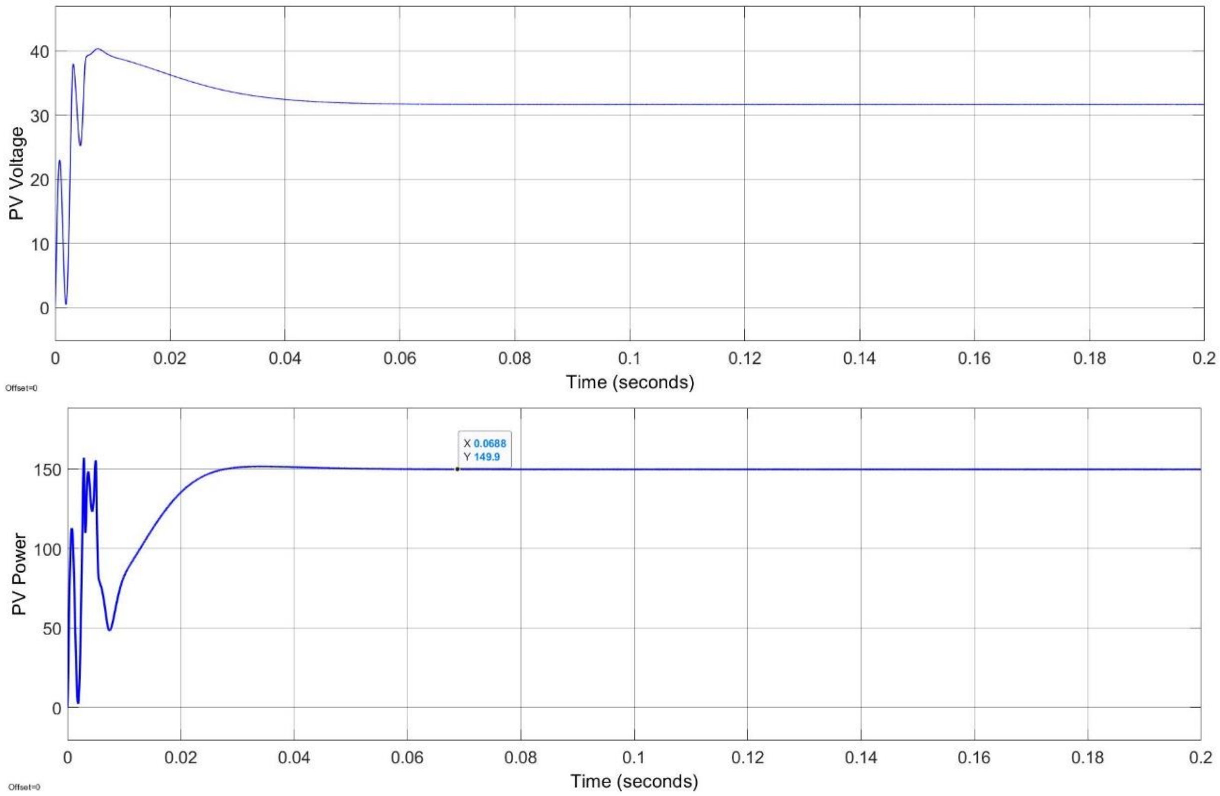
(b)

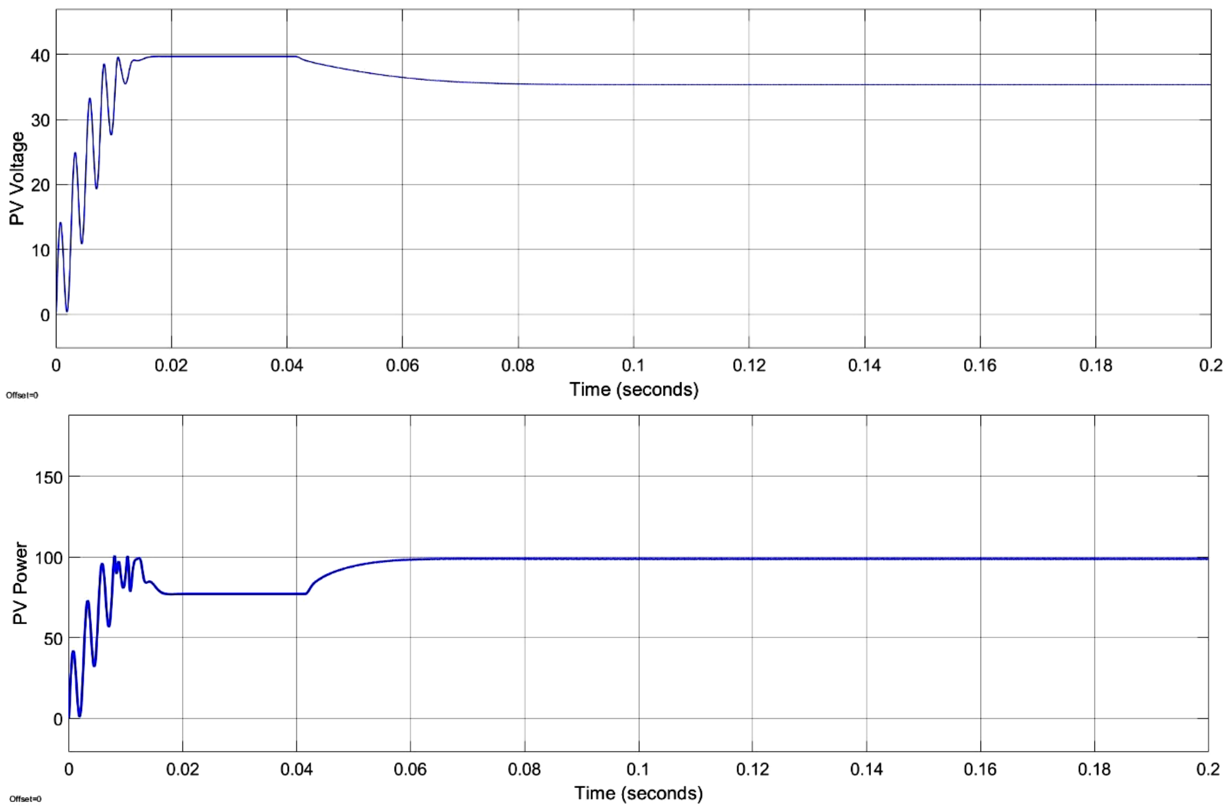


(c)

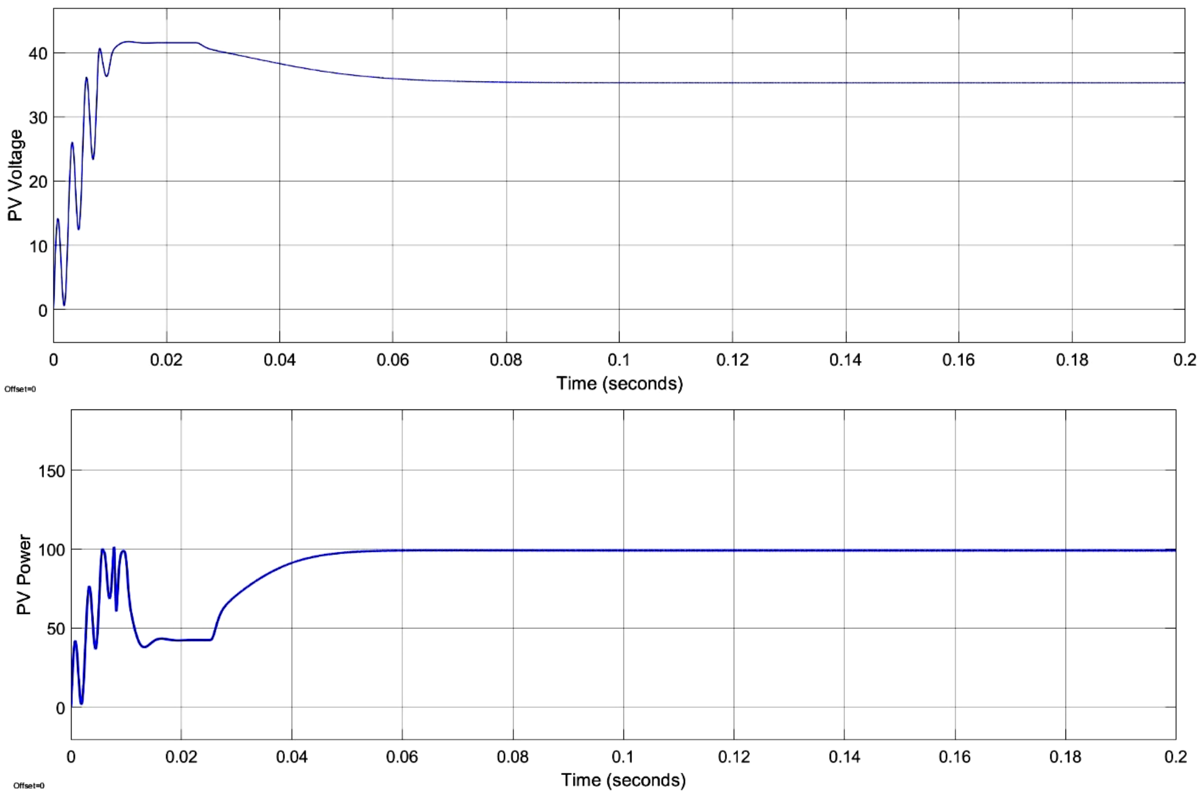


(d)

Figure. 9 PV voltage and power curves for irradiance = 1000 W/m^2 and various values of temperature and resistance: (a) G = 1000 W/m^2, T = 25°C, R = 20 Ω, (b) G =1000 W/m^2, T =25 °C, R =40 Ω, (c) G = 1000 W/m^2, T = 40 °C, R = 20 Ω, and (d) G = 1000 W/m^2, T = 40 °C, R = 40 Ω


PV Voltage
Time (seconds)
PV Power
Time (seconds)

(a)


PV Voltage
Time (seconds)
PV Power
Time (seconds)

(b)

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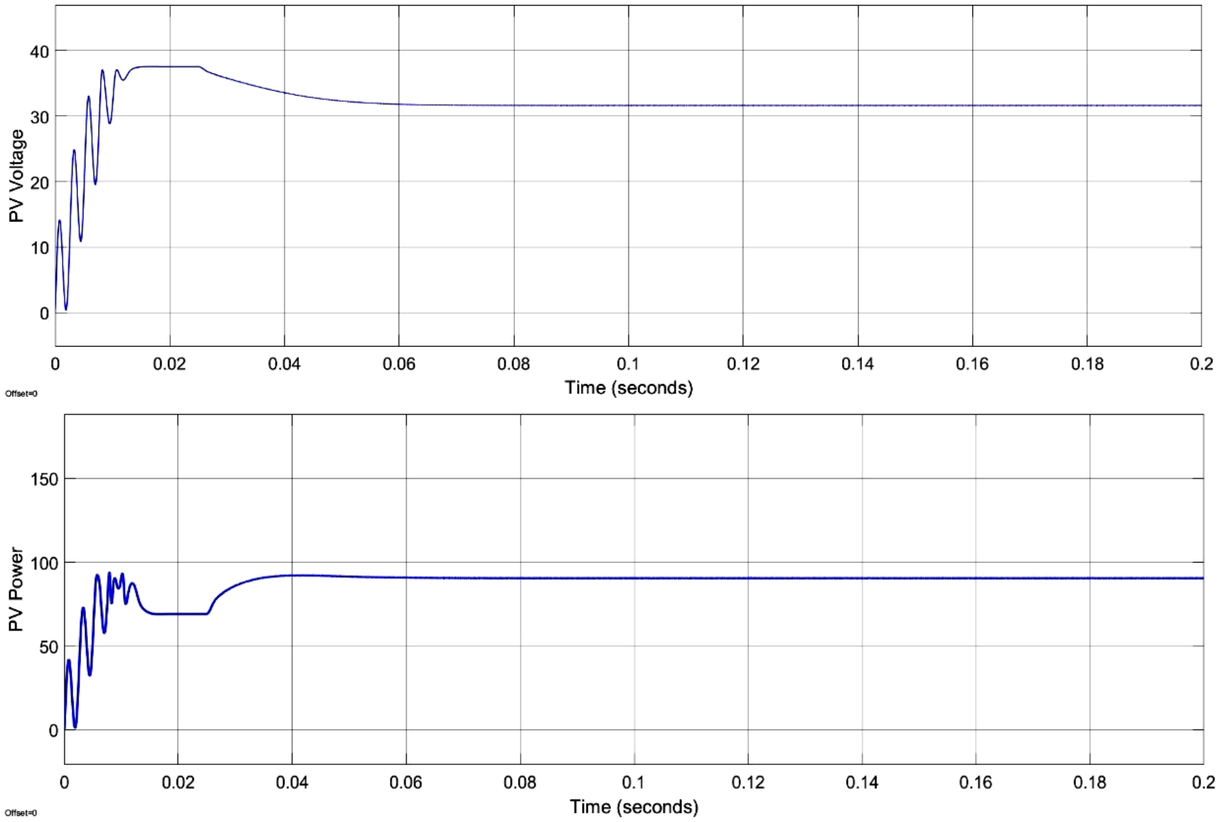
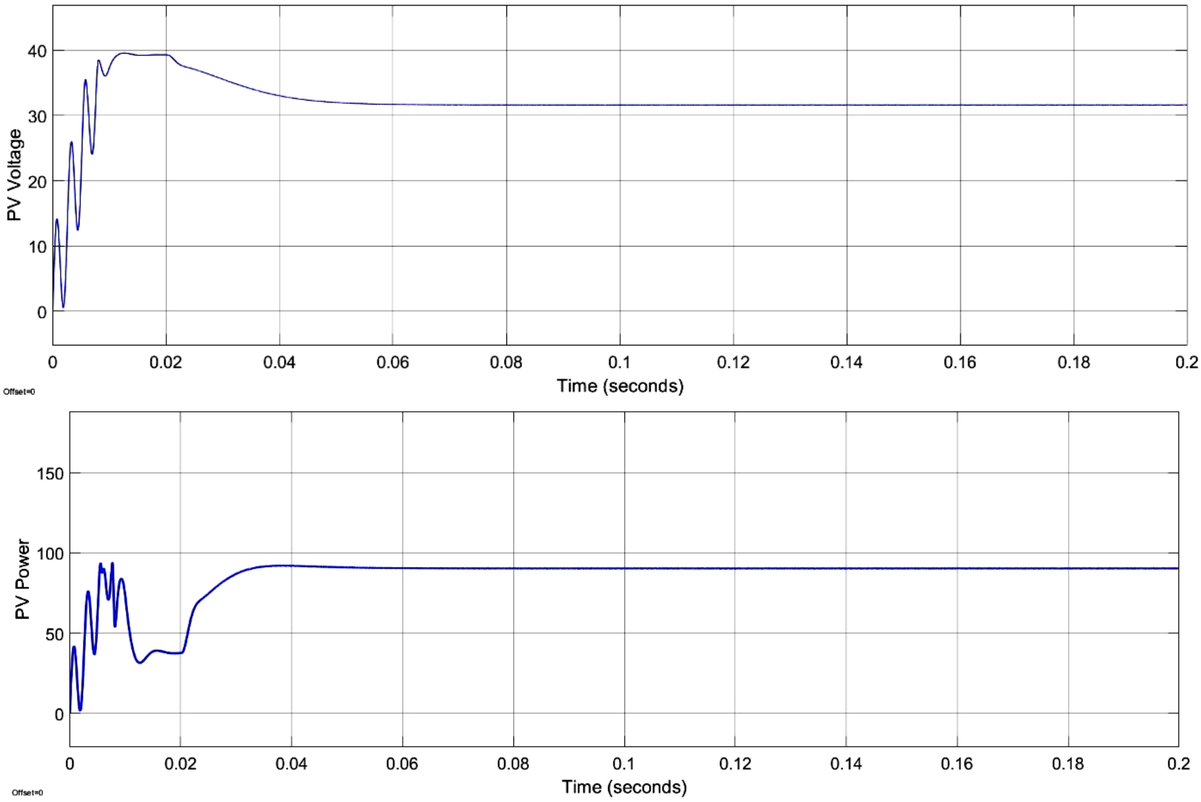


(c)



(d)

Figure. 10 PV voltage and power curves for irradiance = 600 W/m^2 and various values of temperature and resistance: (a) G = 600 W/m^2, T = 25^{o}C, R = 20 Ω, (b) G = 600 W/m^2, T = 25^{o}C, R = 40 Ω, (c) G = 600 W/m^2, T = 40^{o}C, R = 20 Ω, and (d) G = 600 W/m^2, T = 40^{o}C, R = 20 Ω

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Table 4. Summary of PV panel system characteristics results

Irradiance (W/m^2	Temperature (°C)	Load Resistance (Ω)	PV Current (A)	Duty Cycle	Tracking Speed (Seconds)	Max Power (W)	Power at MPP (W)	Efficiency (%)
1000	25	20	4.375	0.3449	0.037	161	162.5	99
		40	4.329	0.5056	0.038	161	162.5	99
	40	20	4.728	0.4222	0.054	148	149.8	98.8
		40	4.729	0.5882	0.069	148	149.8	98.9
600	25	20	2.659	0.1656	0.056	97.34	98.95	98.3
		40	2.663	0.3692	0.048	97.3	98.95	98.3
	40	20	2.859	0.2602	0.073	89	90.47	98.3
		40	2.858	0.4718	0.072	89	90.47	98.3

Table 5. The results of six MPPT techniques

Method	Theoretical MPP (W)	Tracked MPP (W)	Tracking time (seconds)	Efficiency (%)
QNN (proposed)	162.5	161	0.037	99
P&O [5]	160	159	0.05	99.4
Fuzzy Logic [8]	84	79.7	0.03	94.8
ANN and Backstepping Sliding Mode [11]	240	230	0.03	95.8
PSO [22]	854	852	0.186	99.7
mayfly optimization [27]	505	500.4	0.05	99.1

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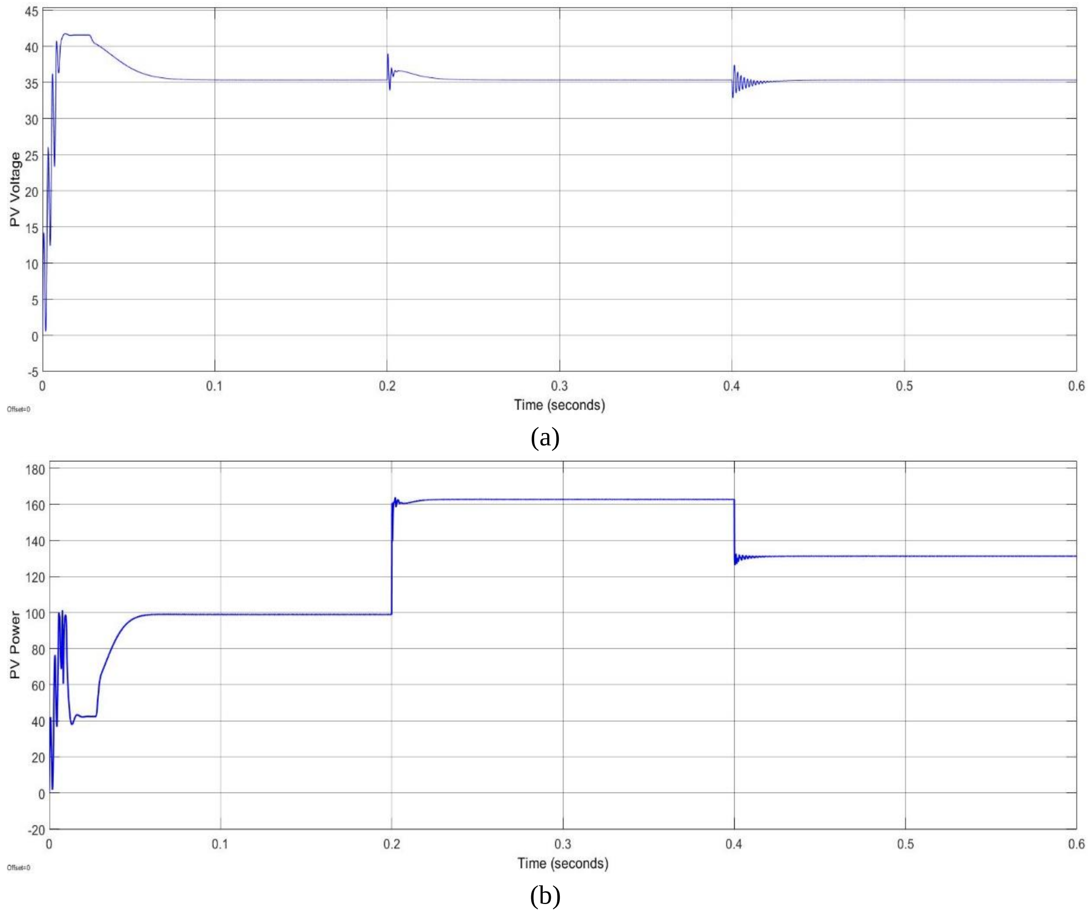

Figure. 11 Long run for irradiance = 400, 1000, and 600 W/m^2: (a) PV voltage and (b) PV power

5. Conclusions.

This work presents the implementation of a quantum neural network as a controller in a photovoltaic solar system to track maximum power point and then deliver the power generated by the panel to the load with minimum losses. To make a complete study on the system with the proposed technique the panel irradiance and temperature and load resistance were varied to check the system efficiency and tracking speed of the power at the maximum point.

The results show no oscillation in the duty cycle curve for different conditions of irradiance and temperature. The highest value of settling time was 0.073 seconds and the minimum efficiency obtained was 98.3 %. It is also clear that the proposed controller complies quickly and adapts to various environmental conditions and it gives better results than those in P&O and PSO methods.

Conflicts of interest

"The authors declare no conflict of interest."

Author contributions

The conceptualization was from Hayder Abdulridha, Mahmoud Shaker and Hussain Jaafar. The methodology was organized by Abdulridha. The software was by Abdulridha and Shaker. The validation was by Abdulridha and Shaker. The formal analysis was by Shaker and Jaafar. The resources were by Jaafar. The data curation was by Abdulridha and Shaker. Writing of original draft was by Abdulridha. Review and editing were by Jaafar. Visualization was by Abdulridha and Jaafar. Supervision was by Abdulridha. Project administration was by Jaafar. funding acquisition is by Abdulridha, Shaker, and Jaafar.

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